Object Control in Virtual 3-Dimensional Space Using ERPs Evoked by Continuous Auditory Stimulation

by

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To my purdy star o' May

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Abbreviations

P300	It refers to the positive peak created in response to a particular stimulus, a usual way to elicit this wave is via the oddball paradigm
ERP	Short for Event Related Potential. Event related potentials are peaks in waves in epoch data by the use of electroencephalography.
EEG	Common abbreviation for electroencephalography, neuroimaging technique used in this study.
Cont-Bench	Comparison bewteen two trajectories corresponding to the continuous condition and the benchmark - Joystick condition.
Disc-Bench	Comparison bewteen two trajectories corresponding to the discrete condition and the benchmark - Joystick condition.
DiscTrim-Bench	Comparison bewteen two trajectories corresponding to the Trimmed Discrete Condition and the benchmark - Joystick condition. The trimming has to do with the data processing that deleted the points in the discrete trajectory where the participant was not moving. See Section 4.1.2.
Rand-Bench	Comparison bewteen two trajectories corresponding one of the 120 random trajectories generated with recorded data and the benchmark - Joystick condition.
BCI	Short form commonly used to describe a brain computer interface.
BBCI	Berlin Brain Computer Interface group. This abbreviation is most commonly used in this paper when it refers to the Berlin Brain Computer Interface toolbox whose MATLAB functions

and routines were used in the experimental design during: signal acquisition, calibration, classification as well as the recorded EEG signals from the people who participated in this study.

UDP The User Datagram Protocol (UDP) is one of the core members of the Internet protocol suite. With UDP, computer applications can send messages, in this case referred to as datagrams, to other hosts on an Internet Protocol (IP) network without prior communications to set up special transmission channels or data paths, according to Wikipedia. They are useful for this experiment because UDPs are the output of choice of the BBCI toolbox and are used to send signals to feedback applications.

OSC Open Sound Control is a content format for messaging among computers, sound synthesizers, and other multimedia devices that are optimized for modern networking technology, according to Wikipedia. In this particular experiment OSC signals were used because they were required to serve as input to the virtual joystick that controlled the feedback application.

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1

Introduction

The technology created by Brain Computer Interfaces (BCI) for navigational purposes, belongs to the area of neuroprosthetics, technology developed as tools for patients with motor disabilities. Certainly, novel applications that have seen the light such as BCI controlled Robots and manipulation of objects in three dimensions are not necessarily developed for clinical populations specifically. These applications include models of drones or helicopters controlled with BCIs that fly in 3D environments (14; 2) which simulate a real flight. Recently BCI controlled flight was achieved with a quadcopter developed at the University of Minnesota, whose technology, according to the news release: "goes far beyond fun and games and has the potential to help people who are paralyzed or have neurodegenerative diseases" [1]. Other innovative use of BCIs is the development of games that have people move objects with the help of BCI inspired technology[2].

Commonly, navigational BCIs use motor imagery and visually evoked ERPs (1; 2; 10) to create signals that allow robots or navigational programs to move. For

[1] ...http://www1.umn.edu/news/news-releases/2013/UR_CONTENT_445216.html

[2] ...http://www.kickstarter.com/projects/1544851629/throw-trucks-with-your-mind

several reasons such as physical limitations in participants, additional modalities other than motor imagery have been and must be explored. One of said models is the AMUSE paradigm which makes use of binary classification that also comes from added spatial information or ”spatial hearing” that makes it possible to use the same spatial information to guide object motion in a three dimensional environment.

The occurrence of the wave P300 is the electrical manifestation product of a complex set of ERPs evoked artificially by the oddball paradigm. In the oddball paradigm, a target previously recognized, in our case, a sound, will be presented among other sounds meant as non-targets in a manner similar to the well known cocktail party effect. Due to the short latency of the P300 wave, a fast presentation of stimuli to the person is possible by stocking stimulus after stimulus with short inter stimulus intervals, and still being possible to classify said waves for further use as it has been shown by Schreuder and others in previous studies (2010, 2011). Other examples of BCI applications include: BCI controlled virtual 3D helicopters using intelligent control strategies (14), Asynchronous BCI controlled car in a virtual reality environment (18), Flying simulated aircraft with EEG (1) and sketches of a P300 BCI based movement (8) mostly designed for neuro-prosthetics and wheelchair applications, in which auditory BCIs are discussed and the potentials advantages and disadvantages are discussed.

The present theoretical framework, however, does correspond concretely to the theories developed by Schreuder, Höhne, Tangermann and Blankertz (17; 16) at TU Berlin. Their ideas explore the development of Brain Computer Interface applications focused mainly in auditory stimulation and BCI spellers, technology which, can be further probed and be helpful for people with certain handicaps, for example, for the use with patients suffering from amyotrophic lateral sclerosis (17) for improving their possibilities of communication (with the use of the AMUSE speller for example. The AMUSE paradigm makes use of multiple binary classifications using auditory

inputs so that participants can have control over word spelling).

2

Theoretical Framework

2.1 Oddball Paradigm and P300 Elicitation

P300 is a wave present in the human brain which gets elicited in response to a rare or unpredicted event in almost any case without prior training. In order to elicit a P300 wave, the oddball paradigm is the most common method used. The oddball paradigm has been used in the previous experiments by Schreuder, Tangermann and Blankertz (17) and it has been reported to have positive P300 wave generation in the brains of participant. Similarly, there have been studies where P300 was elicited by visual stimulation, tactile stimulation, auditory and a combination of both, visual stimulation and auditory stimulation (10). In the auditory case, the method is the following: letters flashing on a screen were used so that participants evoke P300 responses that can be used to train classifiers and posteriorly use the classifiers to compare novel stimuli online. Another experiment was created in which, rows and columns of letters were presented, as in the previous experiment but the letters did not flash, they instead remained unchanged but shown just for reference, in turn participants were told to pay attention to a voice that cued the desired target (10).

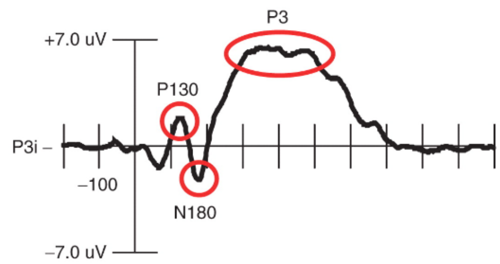

FIGURE 2.1: ERP Complex, ERP components, P100, N200 and P300 are marked with red for better visualization. Taken from url http://scan.oxfordjournals.org/content/2/4/323/F2.expansion querry: Oct 27 2013

Both are examples of proven methods to create P300s. In the current study, auditory stimulation using the best experimental conditions and design were chosen to create a viable experimental setup that can be used for P300 spatial navigation, namely the use of spatial hearing and the AMUSE paradigm.

2.2 Spatial Hearing

According to Schreuder (2010) the direction that the acoustic stimuli come from adds additional information about the stimulus that elicits the P300s waves in the brain. The advantage of the Spatial Hearing is that: "Localization of sounds in space is [a] process that our brain does without mental effort, several studies show the ability of human listeners to distinguish sounds in space when subjects focus on a particular direction, [attention appears] to be distributed in a gradient, with decreasing alertness, when [they are] moving away from the attended direction" (17). With this idea in mind is it possible to create a navigational ERP based BCI on spatial hearing, in which, the directions used for spatial hearing will be the same used for navigation later on. In order to achieve an experiment based on spatial hearing the desired locations will have to be placed accordingly.

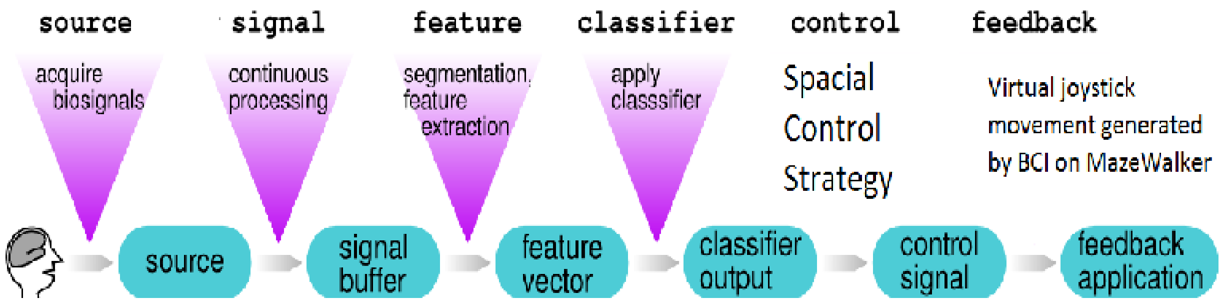

FIGURE 2.2: Online BCI data pipeline. Adapted from the Wiki of the IDA Group

2.3 AMUSE Paradigm

According to Höhne 2011 (12) "the AMUSE paradigm (Auditory MUlticlass Spatial ERP), as presented in [Schreuder et al., 2010], was adapted for online text writing. It consists of a ring with 6 audio speakers around the subject, which produces stimuli in a pseudo random order. The inter stimulus onset interval (ISOI) was 175ms with each tone lasting 40ms".

The AMUSE paradigm has six steps: sourcing, signal processing, feature extraction, classification, control and feedback. For this study, only four of the steps were taken from the AMUSE paradigm described by Höhne et. al (2011). Control strategies and feedback phase due to the navigational nature of the study were transformed. The mentioned steps had to be altered in the following way: a) in the control phase a new control strategy was created that permitted participants make use of their signals to move around in the maze and b) the signals were sent to the feedback application which consisted of a 3D game engine that was developed for maze design, analysis and presentation

2.4 ERP Spatial Hearing Based Navigation

Spatial hearing based navigation can be explained in the following way: by taking the classification scores generated by an algorithm or classifier previously chosen.

Depending on the accuracy of the algorithm and the classification score particular to the participant, it is possible to generate meaningful movement to a certain direction selected by the participant. It is possible to make use of two different modalities to achieve movement:

2.4.1 Continuous Online ERP Classification

Taking the ERP classification scores from a participant and appending them continuously in a unified stream of classification data, a movement command can be produced in the following way. Based on the classification data flow, the challenge is to create an algorithm that deals with dimensionality dissimilarities and sifts incoming data into a stream of movement commands in two or even more dimensions if desired by simply comparing the stream of data to the calibration data recorded previously. The translation from classification values into movement or vector values will have to take into consideration not only the most recent classification but older classifications as well. So having a window of classifications from the most recent toward the past is the way in which the control algorithm makes sense of what direction a participant wants to go to. In bio-signal terms, this means, to select EEG calibration bio-signals that resemble more to the window of more recent online signals. By using Continuous Online ERP Classification, it will depend on the number of speakers assigned for a certain dimension whether the BCI will is able to move in a 2D environment or a 3D environment.

2.4.2 Discrete Online ERP Classification

Taking the ERP classification scores from a participant in a single round of classification and by grouping them in a single block of online classification data, a movement command can be deduced. Based on a block of data from a classification round of n-iterations, we will run an algorithm that simply deduces the direction intended

to move giving commands only in the direction the participant desired to move in a binary fashion (either go to a certain direction or not). In the same way with Continuous Online ERP Classification, it will depend on the number of speakers assigned for a certain dimension whether the BCI will is able to move in a 2D environment or a 3D environment; only that under this condition it will be able to move in a step-by-step fashion, or more precisely by calculating classification-round-by-classification-round.

3

Experimental Methods

3.1 Experimental setup and Data Acquisition

The present study was conducted under supervision of Michael Tangermann and Martijn Schreuder. All experiments were conducted within the laboratories of the BBCI group of the Machine Learning department at the Berlin Institute of Technology. The participants provided their written informed consent to participate in the study according to the approved procedures set forth by the lab and approved by this study's supervisor.

Seven participants, five females and two males between the ages of twenty one and forty with a mean of 29 years old took part in the experiment. Only one of them had previous experience with auditory BCIs. The feedback was generated by Maze-Walker with custom build mazes. The appearance and demeanor of Mazewalker was similar to that of a video game. For that reason a screen was positioned in front of the paticipants. To facilitate movement and spatial hearing this setup can be described as: Participants sat in front of a computer screen. They were surrounded by five active speakers pointing to 90, 45, 0, 135 and 180 degrees from the partici-

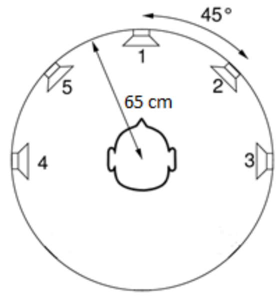

Figure 3.1: Schematic of the experimental setup. Adapted from Schreuder et.al. 2010. Each speaker represents a desired direction in the maze shown in Figure 2

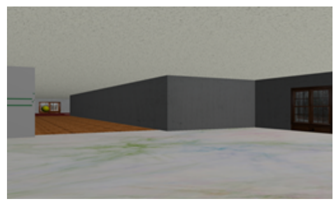

Figure 3.2: A screen capture taken in the first level of the house maze. Movement controls are: X Axis: Rotating Left: speaker 4; Rotating right: speaker 3. Z Axis: Moving forward: speaker 1;. Combined Movements: going forward while turning left: speaker 5; going forward while turning right: speaker 2

pants perspective (Fig. 3.1). The distance separating the participants head and the speakers was around 65 cm, this is to assure that the spatial hearing locations will resemble the most to the original experiment and follow ups by Schreuder and others. The monitor will show a 1st person perspective in a 3D environment through which participants were asked to navigate, the images of the 3-Dimensional environment will similar to the one shown in Fig 3.2

Speaker number four and number three corresponded to the X axis. Whenever the participant paid attention to either of these speakers the camera will rotate to either the left (represented by the speaker four) or to the right (represented by the speaker three). In Turn whenever a participant wanted to move forward, he was asked to attend to the frontal speaker. Left-forward and right-forward movements were also possible by dividing the classification score into X and Y values. In the

online phase of the experiment, online stream of bio signals that source from the EEG will be classified and after passing it through a spatial control strategy algorithm, the BCI will be able to recognize the desired location of the movement which will be the same as the speaker the participant is paying attention to.

EEG was recorded using a fixed set of 56 Ag/AgCl electrodes and BrainAmp amplifiers (Brain Products, Munich, Germany). Electrooculogram (EOG) was co-recorded with two bipolar channels. All impedances were kept below 15 kohms.) with 32 wet electrodes placed at symmetrical positions based on the International 10 - 20 system. Data acquisition software (BrainVision) was used. The signals were sampled at 1 kHz and filtered by a hardware analog band-pass filter between 0.1 and 250 Hz before being digitized and stored for offline analyses. For online use, the signal was low-pass filtered below 40 Hz, down sampled to 100 Hz and streamed to the online Berlin BCI system. The overall set-up of the BCI and starts with EEG signals obtained from the operator via single-montage surface electrodes are processed by a computer using windows 7 x64. The nasion was used as reference point. The referencing used for the calibration was the same for the online feedback as for the offline ERP analysis. Event-related potential classification was performed over these signals using the BBCI toolbox. The amuse paradigm initial steps processed the data used for classification that produced values that could be used as movement inputs afterwards.

Signal Processing, classification and EEG posterior analysis was only possible thanks to the Berlin Brain Computer Interface Toolbox developed by the Machine Learning and Intelligent Data Analysis group at the Berlin Institute of Technology. For detailed implementations refer to the BBCI - IDA publications on the link below [1] . The experiment consisted of six blocks which will be described next.

[1] . . . The full list with the publications by the IDA group at TU Berlin is at: `http://doc.ml.tu-berlin.de/publications/`

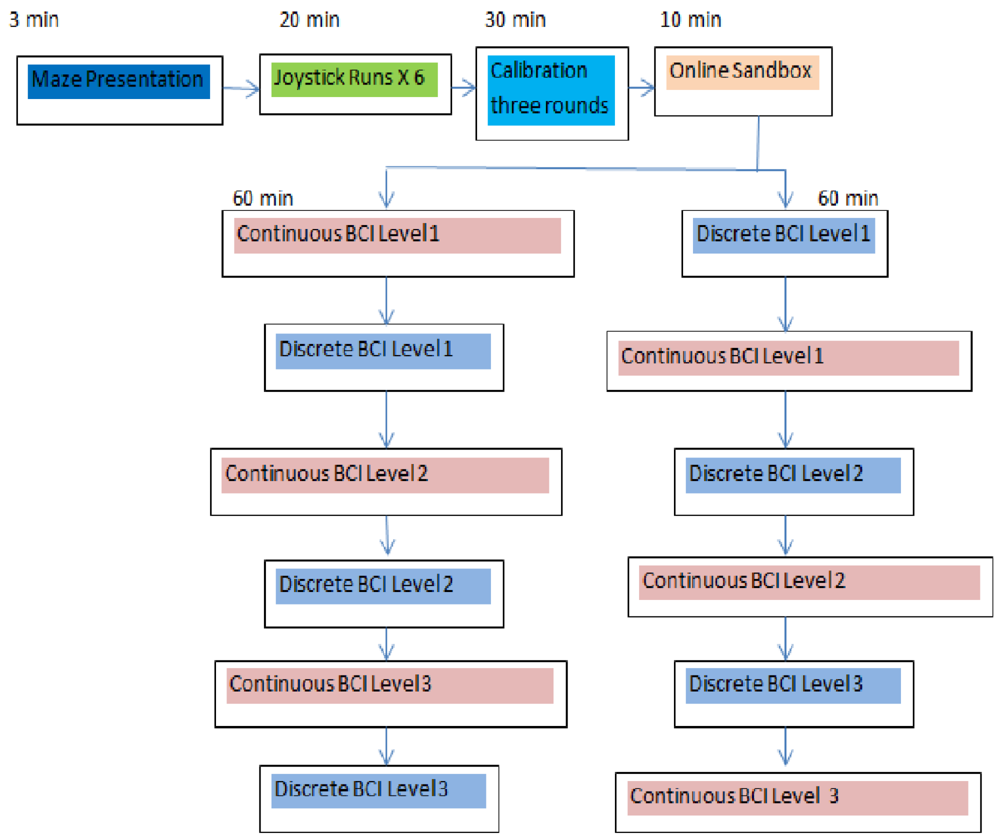

FIGURE 3.3: Flowchart explaining the Stages in the Experiment

3.2 Experimental Task Design

3.2.1 First Block

It can also be labeled as free exploration. Participants were asked to explore the mazes using a joystick and they also were instructed to find the objects to be collected, which, in all the mazes, consisted of yellow spheres which turn blue once touched. The spheres were at certain places signaling subjects the "optimal" or shortest path in the maze, the yellow spheres were included in all the experimental as well as in exploration mazes. Additionally, they were asked to learn and remember the locations of the rooms, objects and corners of the rooms and the locations of where they began and where they ended. The objective of this block was to have

the participants try out the maze and help them remember the maze so that they know what is present in every maze before any recorded trial started. Data from this section was not included in the analyses. .

3.2.2 Second Block

Two complete runs of each level using a joystick. The whole experiment had three mazes with outdoor and indoor scenarios (See appendix 1). Every level was repeated twice by each participant. This measurement was used as the benchmark measurement, useful to compare the optimal performance that a person can achieve in a maze situation using more conventional devices, in this case a joystick. This performance was used as the benchmark, as was pointed out earlier on, in order to have a value, in this case a trajectory that can be used to compare performance to. We used the same mazes presented during the first block.

3.2.3 Third Block

Three calibration rounds using auditory stimuli presented and recorded from subjects. Each speaker had a unique sound identity (easily differentiable from one another varying in tone and other characteristics) so that directions and location in space could be distinguished more easily, so was source discrimination from one another. The calibration of signals were done with the exact same specifications of the experiments by Schreuder et. al. (2010) and Höhne et. al. (2011).

During the calibration phase, each trial consisted of 15 pseudo-random auditory sequences from each speaker. There was no visual stimulation that could aid classification. The presentation of one tone stimulus and the corresponding EEG data (with an epoch of 800 ms after auditory stimulation) will be called sub-trial from now on. The volume of the speakers was slightly attenuated to help the participants concentrate during long periods of auditory BCI navigation because blocks can last

up to 10 minutes each. Thus a single calibration round yielded 5 X 15 sub-trial epochs (15 target sub-trials and 4 X 15 non-target subtrials) available for classifier training. Participants were asked to count the targets and to report the number of occurrences at the end of each trial (counting task). A simple minimum/maximum-threshold method was applied to exclude epochs that included artifacts from the calibration data: epochs were rejected if their peak-to-peak voltage difference in any channel exceeded 100 uV. Data calibration is done automatically by the toolbox and it is not recommended to tweak parameters in the calibration data manually, however, there exist other settings belonging to the calibration sub functions but for this study the default parameters were kept. Three calibration rounds were performed in order for the classifier to ensure performance.

3.2.4 Fourth Block - Online Sandbox Navigation

This block consisted of two square-shaped mazes with pictures onto the walls. The task, too, was to explore the maze only that by using the BCI. The emphasis was on exploring and getting used to the auditory BCI in both conditions: discrete and continuous. In order to achieve that, there was one maze with different items for the discrete condition and one maze different items for the continuous one.

3.2.5 Fifth Block - Discrete Auditory BCI

All three mazes used for the first and second blocks were used for the discrete condition as well. It is worth noting though, that the first experimental condition, either discrete or continuous was picked at random and that the second maze would be in the other experimental condition to alternate conditions. For example: picked at random continuous level 1, later discrete level 1, later on continuous level 2, etc. So in principle any condition could be picked first and both conditions were alternated since then.

3.2.6 *Sixth Block - Continuous Auditory BCI*

All three mazes used for the first and second blocks were used for the continuous condition as well. They were swapped with the discrete ones.

3.3 Auditory Stimulation

Stimuli selection for this ERP BCI system was built as follows: five tones varying in pitch and tonal character were carefully chosen such that they appear to be as different as possible from each other. Tones were presented via five speakers located at five different directions already described. Each stimulus lasted 40 ms, The stimulus onset asynchrony (SOA) was set to 175 ms. The stimulus presentation, the online Berlin BCI system and the offline analyses were implemented in MATLAB (MathWorks), making use of the Psychophysics Toolbox[2]. Off-the-shelf computer speakers (type Sony SRS-A201) were the speaker used to produce the stimulation. The pseudo-random sequences of stimuli were generated such that two contiguous stimuli did not have the same pitch. Moreover, the same stimulus was repeated only after at least two other stimuli had appeared. The procedure was meant to resemble technical specifications by Schreuder et. al (2010, 2011).

3.4 Signal Classification - Calibration

The calibration phase consisted of an auditory oddball task where the participants were asked to focus on target stimuli while ignoring all non-target stimuli. Participants were asked to minimize eye movements and the generation of any other muscle artifacts during the whole experiment. It is present during the third block of the experiment, the BCI's purpose is to read, separate in epochs and create classifiers based on those data and the labels presented. The labels will correspond to the

[2] ...`http://psychtoolbox.org/HomePage`

speaker the participants were asked to attend their attention toward.

Binary classification of target and non-target epochs was performed using a Linear discriminant analysis (LDA) . These values represented the mean potential in intervals of epochs that were discriminative for the classification task. Due to the large dimensionality of features, a shrinkage method (Blankertz et al., 2011) was applied to regularize the LDA classifier. Sub-trial epochs, after artifact rejection, were used to train the classifier. The classification error for unseen data was estimated by cross validation.

The classifier trigger the classification of the online stream of data. The BCI classifier does the procedure iteratively meaning that it will produce five scores, one for each speaker. Taking this into account, we will want to have data stored in the buffer available for later use. In our case, five classification scores back in time, one for each speaker will be enough, other values were tried but the reason for picking this particular number was because it provided a balanced tradeoff between accuracy and reaction time, in other words, if the data is calculated with more than 5 iterations in the past it then will have a higher accuracy but only for steady data and past values. So if participants wanted sudden changes of direction which is normal for navigation studies the BCI will react too slowly. On the other hand, if the data stored is less than three iterations in the past, the BCI will be too inaccurate because there wouldnt be enough data to make a meaningful classification or prediction.

3.5 Feedback

Posteriorly, signals will be sent to the feedback application to move the subject through the maze accordingly. Additionally, thanks to pilot studies it was found that speaker location will be translated to movement in a better way if the last three classifications are taken through the control strategy instead of the five described in this experiment. The reason for using five was to make the EEG data and

performance more comparable between the experimental conditions (Five in the continuous condition and five in the discrete condition). An additional step is necessary to achieve stability however, classifiers output will be passed through a sigmoid function thusly making it less responsive to values closer to zero; this is done to ensure a certain amount of certainty in the classification before performing any movement. The resulting values will be used as input to a virtual joystick that will perform the desired movement in the maze. Next the BCI procedure just described will be framed inside the BCI paradigm, BBCI toolbox as well as within the peculiarities of the software used

3.6 Experimental Control Design and Other Tools

The AMUSE paradigm, the paradigm chosen for the present study, is based on an application of pattern classification and machine learning techniques. Additionally the physical design made easier for participants to associate sound direction to feedback. To the BCI user, feedback was visually presented on a screen showing the application called: MazeWalker. Posterior movement generated by the BCI was translated to video via UDP - OSC signals originating in MATLAB. Subsequently, the programs GlovePie and PPJoy performed the bridge between the control strategy scores and a joystick-like motion shown in the program. In short, both programs were responsible for conveying and transforming the data that resulted in real time screen movement. MazeWalker is part of MazeSuite[3] which is a free software application designed to create 3D environments. It was developed by the team led by Hazan Hayaz and compiled in C++. This tool permits the developer create 3D environments for later in navigational experiments. The program was originally designed for spatial navigation studies, namely, navigational research using infrared imaging (4). For the current experiment the Brain Computer interface was designed and ran in MATLAB. To

[3] `...mazesuite.com`

interface the BCI software to MazeWalker, additional software was needed[4]. Two programs were used to make the bridge: GlovePie[5] and PPJoy[6]. In principle, PPjoy is designed to be a virtual joystick taking inputs from a variety of external sources other than joystick. GlovePie works in the same way only that this one in particular, allows OSD signals to be received as input. The inclusion of GlovePie was to ensure that real Joystick performance used as a benchmark be comparable in magnitude to any signal coming from the BCI classifier. For more detail about the Open Sound Control specification or the concrete implementation in MATLAB see the OSC documentation. [7]. Three mazes were used for experimental purposes as well as two mazes for familiarization. The purpose of the use of the three mazes was to increase in difficulty as mazes or levels went on `https://github.com/wacax/MasterThesis`.

3.6.1 BCI Spatial Control Strategy

The next steps differed significantly from previous experiments that made use of the AMUSE paradigm such that the spatial control strategy made use of the values gotten from the classifications performed by the BCI, which, in turn, were stored in the buffer in a five times five window each corresponding to one of the speakers / categories. Five scores at a certain time were stored for navigational purposes, both the continuous condition and the discrete condition maintained the same window width with the only difference being the weights. They were changed for the continuous condition. In the continuous condition older classifications were assigned lower weight to make more meaningful the most recent classification without excluding

[4] . . . This additional step necessary to create the bridge might no longer be needed in future versions of Mazewalker because it will include Net support according to its creator

[5] . . . `sites.google.com/site/carlkenner/glovepie`

[6] . . . `https://github.com/wacax/PPJoy` PPJoy sofwares development was abandoned by its creator, a copy of the source code can be found this on thesis github repository

[7] . . . For further references about Opensound Control refer to: `http://opensoundcontrol.org/introduction-osc`

totally previous data.

The theoretical principle directing the BCI spatial control strategy, the fifth step on the online BCI pipeline is that raw classifications coming from the BCI flow in a seamless stream of data have intrinsic information indicating the location of the speaker that the participant paid attention to. In order to translate this multi-class information into a continuous joystick-like stream of data we decided, after doing some testing, take the classifications from the three latter iterations. However, for comparison purposes (with the discrete condition principally), the window was widened to five. This process yielded a matrix of dimensions: 5 by 5 containing the classification for each speaker during the last five rounds. In order to get a continuous composed vector in two dimensions containing a value in the axis Y, meaning thrust and in the axis X, meaning heading the following method was chosen: Firstly a multiplication stored in the buffer or buffered classifications times some predefined values took place so the continuous condition can deal with the streaming data. The three most recent values buffered werent penalized whereas the two remaining were multiplied by 0.2 and 0.1 respectively to assure that as little information as possible from old classification scores was conveyed to the final calculation.

$$weightsVector = \begin{bmatrix} 0.1 & 0.2 & 1 & 1 & 1 \\ 0.1 & 0.2 & 1 & 1 & 1 \\ 0.1 & 0.2 & 1 & 1 & 1 \\ 0.1 & 0.2 & 1 & 1 & 1 \\ 0.1 & 0.2 & 1 & 1 & 1 \end{bmatrix}, \tag{3.1}$$

times

bufferedData is a 5 times 5 matrix containing the results from the classifier or:

$$bufferedData = \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{14} & x_{15} \\ x_{21} & x_{22} & x_{23} & x_{24} & x_{25} \\ x_{31} & x_{32} & x_{33} & x_{34} & x_{35} \\ x_{41} & x_{42} & x_{43} & x_{44} & x_{45} \\ x_{51} & x_{52} & x_{53} & x_{54} & x_{55} \end{bmatrix}, \tag{3.2}$$

In the discrete condition there was no initial penalization because all five rounds provided equally valuable data since the participant was asked to pay attention to the same speaker in order to move to the desired direction as opposed to the continuous condition where intentions can change on the fly.

Secondly, the product of this penalization was subjected to a filtering through a sigmoid-shaped function. The Sigmoid membership function [8] is calculated on the values of the product corresponding to the product of weightsVector times buffered-Data, this step is necessary to ensure that small values that don't reach a certain threshold cannot be transformed into movement, thus getting rid of non-relevant data that was probably misclassified or appeared in the stream due to other circumstances.

Values "a" and "c" are tunable data to ensure that the output limits of the sigmoid function fall within desired values

$$f(x, a, c) = \frac{1}{1 + e^{-a(x-c)}} \tag{3.3}$$

Where the value x belongs to every single element of the weightsVector times bufferedData matrix.

Moreover the additional step that had to be performed, given that values might jump from positive to negative and vice versa when the result of the aforementioned multiplication approximates zero but is not exactly zero. Then a sigmoidal-shaped

[8] ...The sigmoid membership function was picked because it can be tuned to its lower value be around zero and the maximum value be 1, the concrete implementation was inspired by the formula found here: `http://www.mathworks.de/de/help/fuzzy/sigmf.html`

function was included to smoother the movement when the classification was not clear nor the values were large enough, making the output of the function a value close to zero. However, when there was indeed a clear classification, the function will output a non-lessened value and even if its input value was high compared to other subjects; it also will be rounded toward one. As a consequence, filtering through a sigmoid function softened movements making them clearer and less sensitive to misclassifications, outliers or environmental flukes when classification was not clear enough. Additionally, it capped the velocity to a maximum value when the classification values had gone too high. This also helps achieve motionlessness when the participant was not paying attention to any direction. The whole implementation in MATLAB can be found linked in the experiment's repository on github.

Thirdly, five sets of weights conforming to the directions indicating where to travel were selected based on performances of pilot experiments. Each of the directions' weights will correspond to a particular speaker, which, in turn, will have to be converted into a discrete value in X and Y axes respectively. The speaker will have two values: one corresponding to X and one corresponding to Y. The following nomenclature matches the figure 3.1 with the spatial distribution of the speakers in space. These directional weights will be fixed so that an iterative remapping to a XY space, 2 dimensional axes, can be performed. It can also be thought of a dimensionality reduction thanks to a matrix multiplication between values from the buffer and weights corresponding to XY axes and ignoring the non-relevant values. The axis Y would match up to forward movement whereas positive axis X would correspond to a right turn and negative axis Y would correspond to a left turn.

Front - Forward, Speaker 1

Value in X = 0; value in Y = 1.25

Right Turn plus Forward Movement, Speaker 2

Value in X = 0.75; value in Y =1

Turn Right, Speaker 3

Value in X = 1.25; value in Y = 0

Turn Left, Speaker 4

Value in X = -1.25; value in Y = 0

Left Turn plus Forward Movement, Speaker 5

Value in X = 0.75; value in Y = -1

Directional values can therefore be expressed as a matrix of dimensions 5x2. Let's call it from now on: directional matrix.

$$DirectionMatrix = \begin{bmatrix} 0 & 1.25 \\ 0.75 & 1 \\ 1.25 & 0 \\ -1.25 & 0 \\ 0.75 & -1 \end{bmatrix}, \tag{3.4}$$

The directional matrix's values shown here can be changed according to the particular needs of the setup; though, the positive and negative values ought to remain unchanged for the BCI to move toward the desired directions.

Next the remapping is done with a matrix multiplication:

$$SigbData = \begin{bmatrix} f(x,a,c)_{11} & f(x,a,c)_{12} & f(x,a,c)_{13} & f(x,a,c)_{14} & f(x,a,c)_{15} \\ f(x,a,c)_{21} & f(x,a,c)_{22} & f(x,a,c)_{23} & f(x,a,c)_{24} & f(x,a,c)_{25} \\ f(x,a,c)_{31} & f(x,a,c)_{32} & f(x,a,c)_{33} & f(x,a,c)_{34} & f(x,a,c)_{35} \\ f(x,a,c)_{41} & f(x,a,c)_{42} & f(x,a,c)_{43} & f(x,a,c)_{44} & f(x,a,c)_{45} \\ f(x,a,c)_{51} & f(x,a,c)_{52} & f(x,a,c)_{53} & f(x,a,c)_{54} & f(x,a,c)_{55} \end{bmatrix} \tag{3.5}$$

times

$$DirectionMatrix = \begin{bmatrix} 0 & 1.25 \\ 0.75 & 1 \\ 1.25 & 0 \\ -1.25 & 0 \\ 0.75 & -1 \end{bmatrix}, \quad (3.6)$$

The result of this matrix multiplication will be a 5x2 matrix, each row with a value relating to X on the first column and a value relating to Y on the second column. Posteriorly, the arithmetic mean of the values is calculated for the 5 iterations and the result will be a vector of length two with one value for X and another for the Y axis. This result will be the XY score at a particular time.

PacketValue(t) = [Value in X Value in Y]

Additionally, and this assertion is probably the most important differentiation between discrete and continuous conditions is that, in the discrete condition, instead of yielding a numeric value with any value from zero to one, it will yield a value of either one or zero. So if the discrete condition is selected after the mean calculation aforementioned, only the sign is taken into consideration because it only will be able to output of either positive or negative one or zero.

PacketValueDiscrete(t) = [binary Value in X binary Value in Y]

3.7 Frechet Distance

Commonly used for other applications such as writing recognition, the Frechet Distance makes a good metric for the present trajectory analisis. The difficulty of calculating two curves with the same length or with the same amount of points reside in the distance metric used; different methods have been proposed for that matter, when comes to curves without the same length; however, a different approach must be taken because other distance metrics assume two lines with the same amount of points in a given coordinate space. For this issue there are two alternatives at hand,

in video, audio or any other type of combined media the most common method is the dynamic time wrapping. For instance: three songs, three sets of waves, the first one recorded in a concert, a second recorded in a studio and a final one at a different studio will have a smaller distance between their waves when compared to others such as another song or the recording of a train passing by. Following the same train of thought we realize that measuring two curves is possible by comparing their dissimilar lengths in a systematic way. Given that the trajectories traced by the participants will only contain data in 3D, there is no need of going as far as calculating their distance using dynamic time wrapping. We ought to, instead, make use of a simpler metric the Frchet Distance because we are not interested in the analysis of the subtleties of sound and/or melody that such a procedure can entail.

This metric, which can map many points in time to a single point in the optimal path, it can be better understood through the following analogy: when a dog is strolling with its owner, both are linked by the dog's lash. The owner can be standing at a particular spot while the dog can wander around to many different places at various moments. The different places the dog can wander will be mapped to a single point on the trajectory of the owner, namely, the closest one (imagine when the dog owner is standing still). In the experimental case this will be mapped to the optimal path, thus giving us the following:

The reparametrization between the boundaries of 0 and 1 is needed for this metric so all values at time = t will be within the range of 0 and 1; d being the distance function, in this case we will keep it simple so we will maintain the Euclidian distance.

$$F(A, B) = inf_{\alpha,\beta}\, max_t\{d(A(\alpha(t)), B(\beta(t)))\} \tag{3.7}$$

In a thorough yet simple explanation:

The Frchet Similarity index is equal to the Infimum (or lowest value) of the highest

number at time = t belonging to the interval between zero and one (reparametrization) defined as:

$$t \in [0, 1] \tag{3.8}$$

, thus d or the Euclidian Distance of the point a of trajectory A at time t or A(a(t)) and the point b of trajectory B at time t or B(b(t)) will be repeated for all the points on the trajectories[9].

A detailed example is presented in fig. 3.4:

The Frechet distance in this example is the mean of all the distances between points, the Frchet distance can be seen as the yellow line in the lower left corner being compared with the size of the original curves. This method has been discussed in Aronov A. et.al Frechet Distance for Curves, Revisited.

[9] ... The concrete implementation was taken from `http://www.mathworks.com/matlabcentral/fileexchange/31922-discrete-frechet-distance`

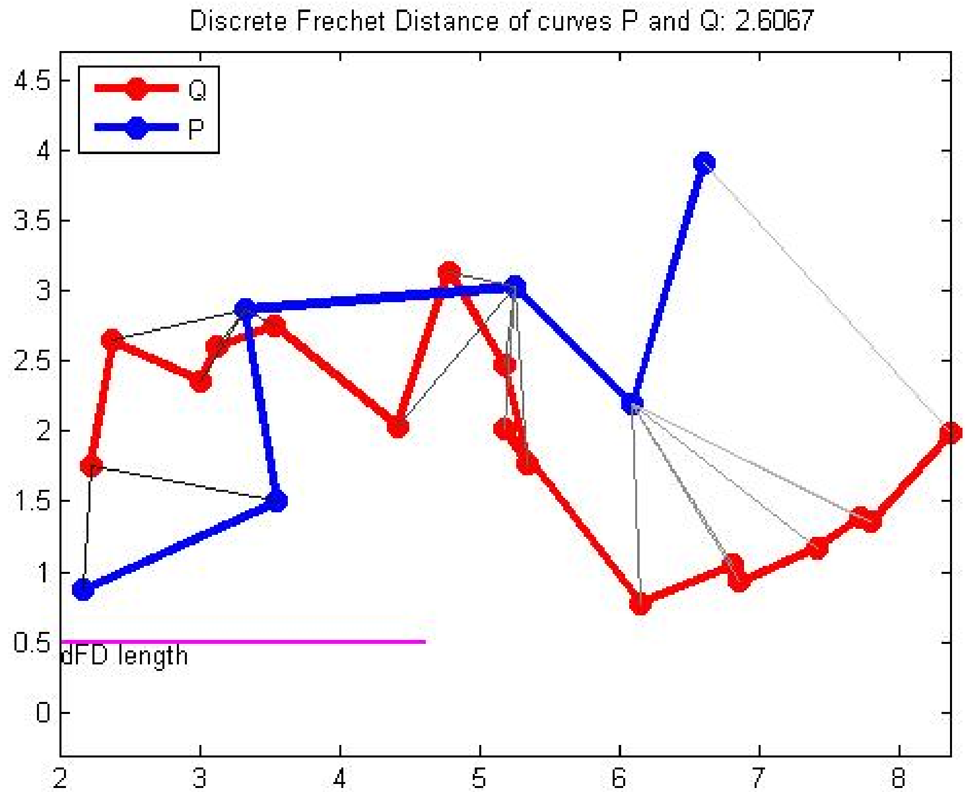

Figure 3.4: Discrete Frechet Distance calculated between two trajectories. The pink line representing the overall Frechet Distance value between curves Q and P represents the mean of the distances between all the points pertaining to both trajectories,. (2.6067) here represented in light gray.

4

Analysis and Results

4.1 Experimental Contidions

BCIs performance was calculated across carefully chosen conditions that compared a baseline or a benchmark with random results and with experimental conditions' results:

4.1.1 Random Condition

The random condition is the result of 120 runs of the experiment without a participant. Although in this condition synthetic data was sent from the BCI recorded from a participant during the pilots. The data fed was produced by picking randomly one sample of certain category (or a label corresponding to a given speaker) and repeating it for two seconds in order for the data to accumulate in the buffer and be able to move, given that the use of a shorter sequence would have made impossible to move as stored samples would have been too small and even close to zero due to the remapping by the logistic-shaped function. See p.20.

4.1.2 Joystick Condition / Benchmark Condition

A joystick was used as benchmark given its familiarity to many participants and easiness of use. Two repetitions of the same level were used to get a better approximation to average performance of the level by the current participant.

4.1.3 Discrete Condition

The Discrete Condition was recorded when participants used the auditory BCI with five iterations for each speaker and then the BCI system decided a direction to move to. It can only be a binary value of zero (no movement in an axis) or positive or negative one (full movement in an axis).

4.1.4 Discrete Condition

The Continuous Condition was devised in such a way so movement can flow seamlessly opposed as the Discrete Condition in where there has to be a stop for the participant to listen to the stimuli and then decide and classify the direction to where he intends to move.

4.1.5 Discrete Trimmed Condition

This synthetic condition was created offline with additional processing. It is similar to the Discrete Condition in the sense that its trajectory remains the intact but with the only difference is that all time intervals in between movements were deleted.

4.2 Curve Similarity Analysis

The mechanics of this analysis is pretty simple; the Frechet distance calculation between two curves yields a value of similarity. Consequently in this metric, a lower numeric value is to be thought as an indicator of a higher similarity between two curves, the more similar two curves the lowest the Frechet distance. The objective

of the first part of the analysis is to compare both BCI conditions performances to the benchmark in this case using a commonly used input method, a joystick. The distances can be deemed as valid because the distances between the curves in the joystick condition and the random condition is the highest, as was expected; the experimental conditions are supposed to fall somewhere below random performance when compared to the benchmark. For this part, the Frechet distance was used for its ability to give a value to two curves of different lengths and more importantly, between two curves that can move freely and even come back to the initial point as it happens normally in movement trajectories.

4.2.1 Condition Comparisons

Random Benchmark: Firstly, in order to check the validity of the benchmark condition, we used all the 120 trajectories and calculated the Frechet Distance, the similarity between random distances and benchmark distances, thus, having the highest scores when these two conditions were calculated. There were occasionally lower values represented on the plot as outliers, which, of course, represent trajectories that thanks to luck got further than regular random trajectories and even some reached the end of certain rooms (also named as regions). These data points were out of three standard deviations. It is worth noting, however, that there are no higher outliers due to the fact that the time was limited rendering impossible to create outliers with higher Frechet distances because the time was capped and therefore no longer trajectories could be produced.

Continuous Condition Benchmark: The Frechet distance, i.e. the similarity between two curves, in this case continuous trajectory was compared to its respective joystick trajectory for that particular house (ex: continuous condition trajectory in house one compared to joystick in house one for that particular subject and so on)

Discrete Condition Benchmark: The Frechet distance, in this case discrete tra-

Table 4.1: Statistics corresponding to Frechet distances described by condition

Metric	Disc-Bench	Cont-Bench	DiscTrimm-Bench	Rand-Bench
mean	28.66	25.54	25.83	38.55
minimum	6.62	8.09	2.71	8.73
maximum	36.86	47.60	35.21	50.48

jectory was compared to its respective joystick trajectory for that particular house (ex: discrete condition trajectory in house one compared to joystick in house one for that particular subject and so on).

Discrete Trimmed Condition Benchmark: The synthetic trajectories previously created based on the discrete trajectories for each subject was compared to the benchmark trajectories in order to check whether the trajectory without breaks was actually superior in accuracy than the continuous condition. Also this comparison can also be thought of as a potential performance for the continuous condition if a superior and more sophisticated control algorithm were developed.

4.3 Results

For the results of this comparisons of similarity between curves, all the results for each subject in a certain condition was grouped by taking the Frechet Distance of a condition and the Benchmark performance for that particular participant (ex. Continuous Condition in House one vs. Benchmark Condition in House one for that particular participant). Additionally all three results for each participant in a single condition (ex. Continuous in the houses one, two and three) were grouped with the results in the same condition for all seven participants giving us a total of 21 Frechet Distances within each condition.

The bars in fig. 4.1 represent the similarity between the experimental conditions and the benchmark. There is also present a bar representing the similarity between

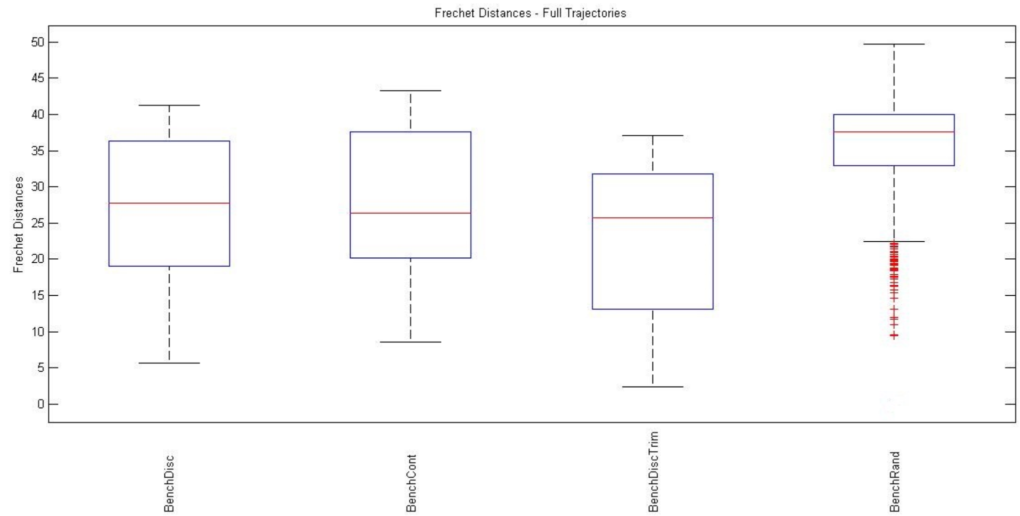

FIGURE 4.1: Frechet Distances between experimentall conditions accross all subjects. BenchDisc: Benchmark-Discrete comparison, BenchCont: Benchmark-Continuous comparison, BenchDiscTrim: Benchmark-Discrete Trimmed comparison, BenchRand: Benchmark-Random Trajectories comparison

the random condition with its 120 trajectories and the benchmark trajectories. In the latter case there wouldnt be 21 data points but instead 420 each of which corresponding to one random trajectory compared to each participants trajectory. (i.e. seven participants times six joystick trajectories times 120 random trajectories).

The explanation for the similar scores in fig 4.1 for the continuous and the discrete condition in the boxplot is that: even though the continuous condition has an effective time of free movement of ten minutes, the actual limit of time in the experiment. Tthis longer duration accounts for the results because it allows the participant to travel much further compared to the discrete condition that has a time of 1.5 minutes of effective movement, having the rest only to stand still and wait for the BCI to classify the brain waves.

For the same reason the Discrete Trimmed Condition was created, notwithstanding, in order for the distances traveled to be more visible and statistically evident,

Table 4.2: Statistics corresponding to Frechet distances in Trimmed Trajectories described by condition

Metric	Disc-Bench	Cont-Bench	DiscTrimm-Bench	Rand-Bench
mean	29.8	29.34	20.83	31.48
minimum	8.68	11.89	3.28	0.4
maximum	32.92	43.40	40.21	50.48

it is also needed to take the same amount of time available in the discrete trimmed condition and shorten the other conditions to the same times (or trajectory lengths). In other words if we were to compare the discrete trimmed with the continuous condition, the continuous condition will still have an advantage in Frechet scores and it will be more similar to the joystick condition because it had more time to roam freely to be more like the joystick trajectory. The Trimmed Discrete Condition couldn't be more similar to that line when both complete lines are considered because in spite of its higher accuracy it cannot be further elongated.

So the Trimmed Experimental Conditions were created by calculating the fastest Discrete trajectory and tacking the same amount of data from the other trajectories until that time. Put it differently, the two experimental conditions: Discrete and Continuous, were cut at the time in seconds as of the fastest Trimmed Discrete Condition in order to include all the Trimmed Discrete Conditions, thereby having more comparable trajectories in length, excluding the extra time the other trajectories had to outperform in accuracy.

So the same calculations were performed using the same conditions but with the only difference that just first segment of the trajectories was used. The results differed in the next grouping as it can be seen in fig. 4.2

The bars corresponding to the experimental conditions as well as the bar corresponding to the random vs. benchmark comparison remained at the same height, meaning that the trajectories are not significantly different among the three if only

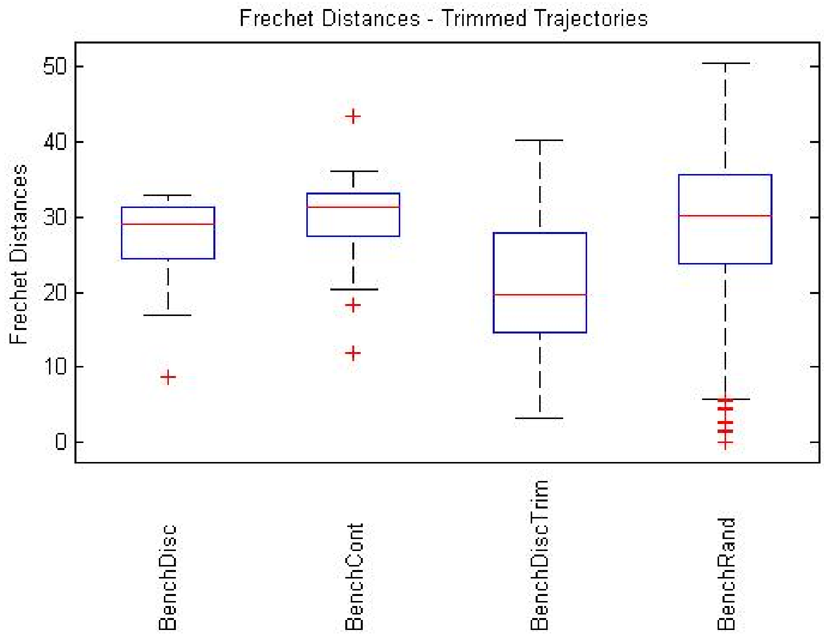

Figure 4.2: Frechet Distances between experimentall conditions accross all subjects at the time it took to the fastest Discrete Trimmed Trajectory for that particular subject to complete. BenchDisc: Benchmark-Discrete comparison, BenchCont: Benchmark-Continuous comparison, BenchDiscTrim: Benchmark-Discrete Trimmed comparison, BenchRand: Benchmark-Random Trajectories comparison

the time needed for the Trimmed Discrete Condition is used. The Trimmed Discrete vs. Benchmark comparison, however, stood out to the other comparisons having a lower distribution in comparison to the benchmark, meaning that it was much more similar to the joystick (benchmark) condition when only the first lapse was used in the calculations as when the full time trajectories were used in the calculations.

The explanation here is rather simple, the experimental trajectories other than the Trimmed Discrete, take longer to develop a similarity to the benchmark whereas the Trimmed Discrete resembles more the benchmark and takes less time to be more similar to the benchmark also, this is certainly a clear indication of higher accuracy in the Discrete condition in general, where, despite its lower speed not because the

speed was capped but due to the pauses in between movements had more precision in movements often comparable to the benchmark. This result can be also understood in terms of potential development of this technology, it tells us that with a more sophisticated control algorithm higher performance is possible and as we will see later on even comparable to the joystick performance in both accuracy and speed.

4.3.1 Preciseness of Full Trajectories and Trimmed Trajectories

An additional way to visualize the previous effect is the following figure (4.3); here the graphics from an upper perspective have an underlying heat map indicating population density. Each point here represents a location where each participant was located during the whole experiment, in each subplot, a different condition is shown. For the random condition 10 trajectories were randomly selected in order to plot the lines more clearly.

The continuous condition resembles more the trajectories of the benchmark, however, if a cut is made at the minimum time needed for the fastest Trimmed Discrete Trajectory to finish the image changes dramatically. See fig 4.4.

In figure 4.4, where, minimal values for each participant are chosen, the trajectories of the Continuous and Random are alike because the continuous Condition, due to its lack of accuracy it does not have the time to advance in the mace and had a hard time bumping onto walls mainly whereas the more accurate condition, the Discrete one, is able to do a better job in a shorter interval, with and without trimming the moments when the movement ceased.

4.3.2 Time and Distance Analysis

The two metrics were extracted indirectly from the log files using the MazeAnalyzer software, part of MazeSuite, which also takes into account natively the experimental maze with its objects within and the trajectories, so no additional preprocessing was

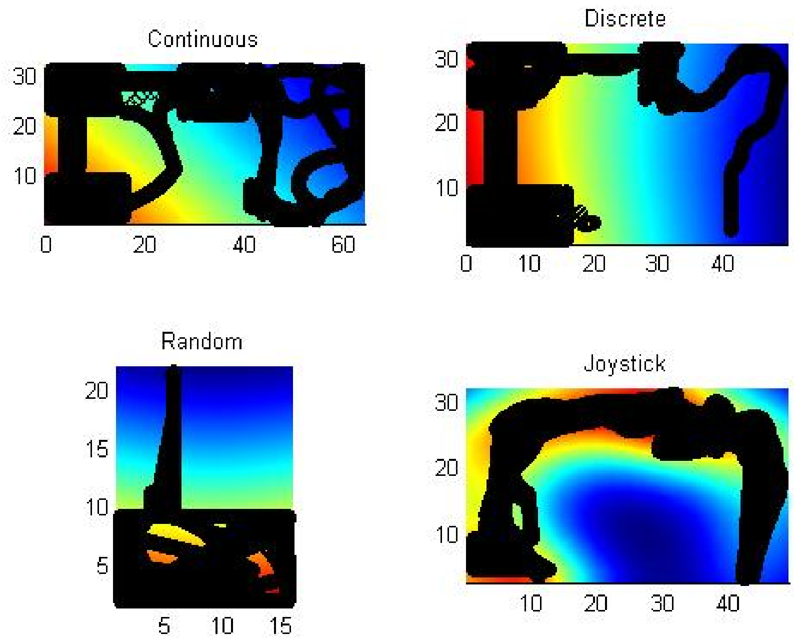

FIGURE 4.3: Upper perspective of the full trajectories, hottest colors denote higher data density around that pixel

needed.

The distance is once again measured in Maze units and the time in seconds, the velocity is relative to both these measures so it is calculated in MazeUnits over seconds. For this analysis the maze was separated into six regions corresponding to the following figures for each house. The reason for that was: path length and time taken from the complete trajectories will be heavily influenced by the time cap, meaning that time will tend to lean toward 600 seconds for the unfinished mazes as well as a certain length, especially, in the discrete condition where in addition to a time cap, there is a moment of immobility, producing similar lengths in unfinished mazes.

As a consequence, the mazes were split into regions to take the time and path length in them, i.e. the time spent and the distance traveled before moving to the

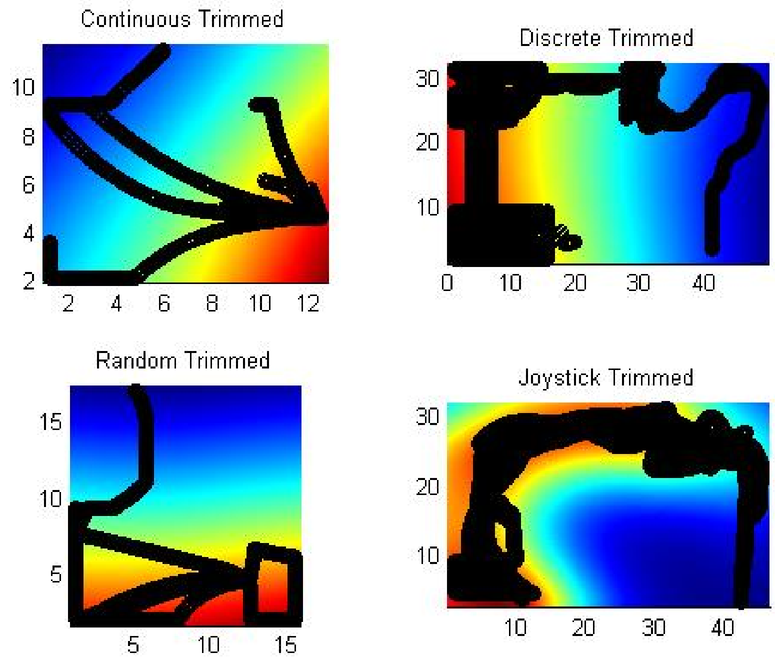

FIGURE 4.4: Upper perspective of trimmed trajectories, hottest colors denote higher data density around that pixel

next region, giving us a better approximation for an uncapped time limit as well as distances that vary according to accuracy and intention of movement.

Given the reasons outlined in the previous paragraph is predictable that the most accurate and precise conditions will have lower time and shorter distances in region one. The results agree with this assumption as is shown in figure 4.6. Here the performance of all subjects in region one is presented with the times and path lengths as metrics. Region one has been selected because its dimensions and layout is exactly the same in all the three houses and it is relatively simple to navigate through.

It is important, however, not to assume the applicability of the same reasoning for all the regions because they vary in different ways such as in objects found inside and even sometimes dimensions. It is worth noting though, that similar results were

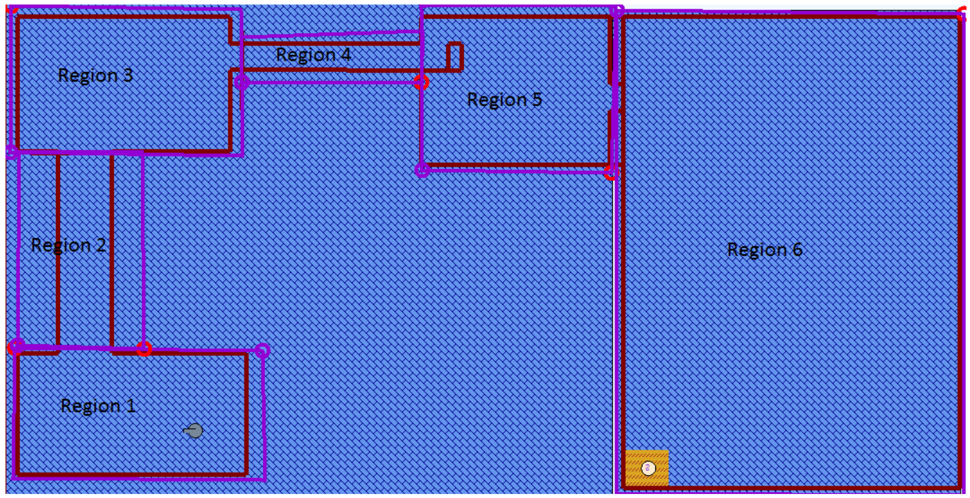

Figure 4.5: Mazes' layout, the three mazes had exactly the same dimensions

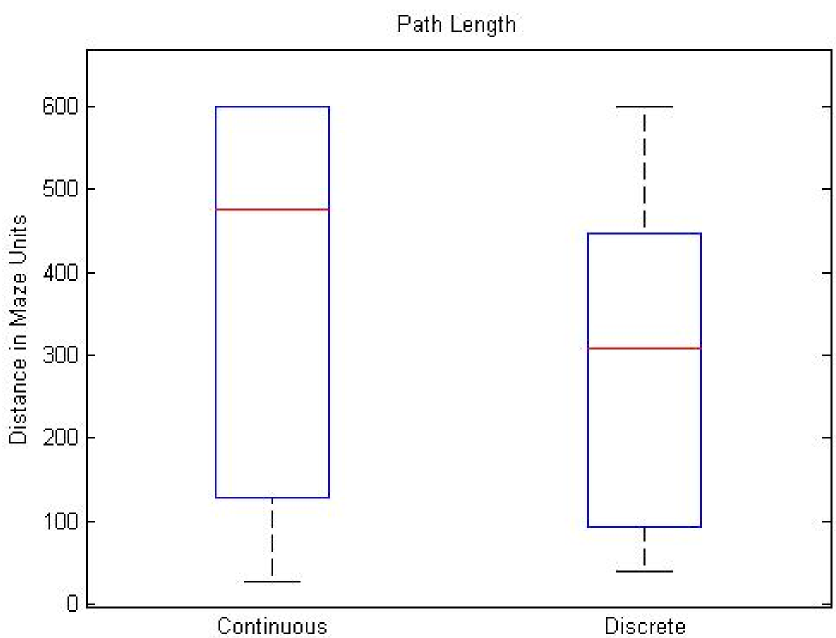

Figure 4.6: Length of the path in maze units in region 1 for all subjects and all houses separated by condition

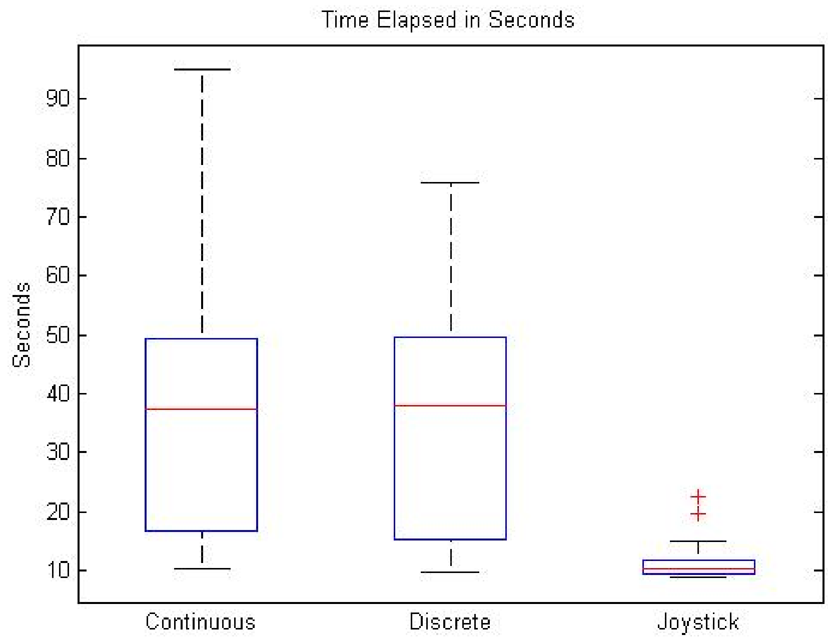

FIGURE 4.7: Time in seconds spent in region 1 for all subjects and all houses separated by condition

obtained when the second and third regions data were collected and calculated, not in the sense of same times and path lengths but in the sense of same distribution and performance compared to other conditions

Table 4.3: Statistics corresponding to Path length and Time in the first region of the maces.

Metric	Path Length Cont	Time Cont	Path Length Disc	Time Disc
mean	402.23	38.11	299.67	36.68
minimum	28.27	10.27	41.01	9.88
maximum	599.97	94.9	599.91	75.66
skewdness	-0.58	0.74	0.14	0.24

4.3.3 Projection onto the optimal Path

In addition to the previous analysis, a quantitative way of measuring performance in percentage is to project the performance of the experimental conditions onto the best possible path and visualize in this way how much it traveled compared to the fastest conditions (Figure 4.8). The procedure for getting the optimal path is rather simple, take the lowest time that a benchmark condition took to finish the maze and sample the same amount of data from the other benchmarks from other subjects, and extract the mean of the points. Later, take the experimental conditions trajectories at a certain time and look for the closest point in the optimal trajectory by calculating the Euclidian distance between the data points of the optimal condition and the point of the experimental condition at a given time, the minimum distance will be the closest to the optimal trajectory, thus having the nearest point to the experimental condition at a given time projected onto the optimal trajectory.

$$Aindex = inf_{\alpha}\{d(A(\alpha(t)), \beta(t))\} \tag{4.1}$$

The mathematical description of the process abovementioned is shown here where A is the optimal trajectory and the point labeled as "beta" represents two points in X and Y respectively that we want to check for the smallest value or infimum across the curve. Moreover, in each condition multiple data points will be present from different participants so the lower and higher bound as well as the standard deviation of these projections will be calculated.

4.3.4 ERP Analysis

A standard ERP analysis over the training BCI data was conducted. The objective of the analysis was to present evidence that the P300 waves presented a similar behavior as the previous studies that such data was used for classification purposes

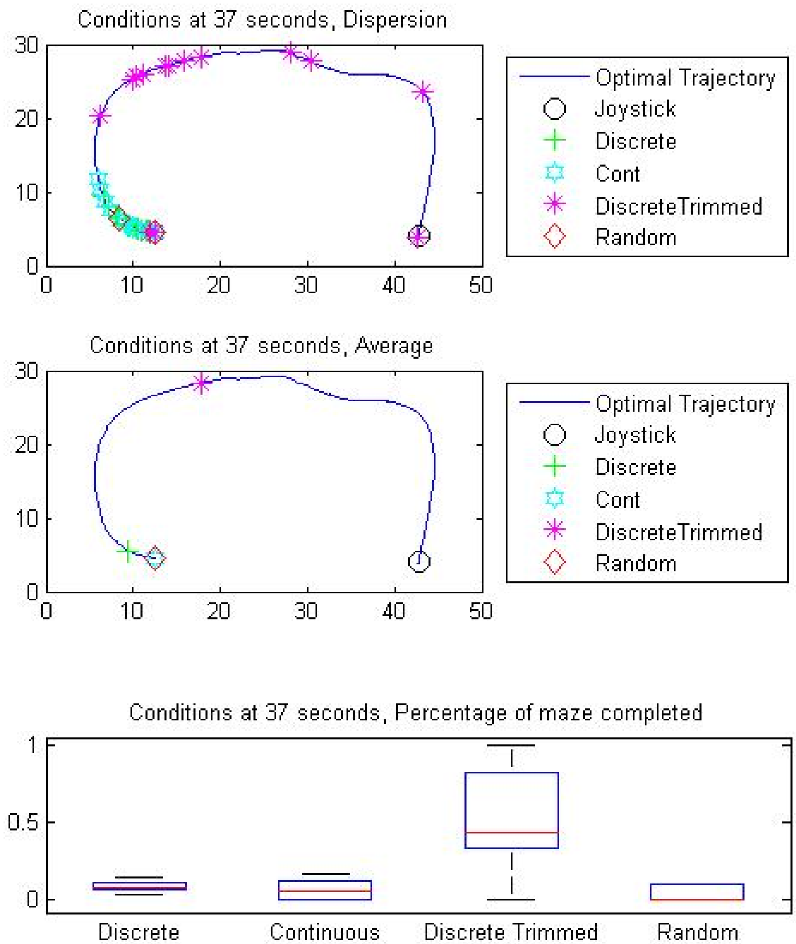

FIGURE 4.8: a) Dispersion of all participants in all houses projected onto the closest point in the optimal trajectory. b) Means across all subjects. c) Percentage of Maze completed at t:37s. The reason this time was chosen is at 37 seconds exactly is the value when the quickest trimmed trajectory would have finished the maze and coincidentally the fastest joystick trajectory also ended at 37s. The mean and standard deviation values for the boxplot are the following: stdDisc: 3%, meanDisc: 8%, stdCont: 6%, meanCont: 6%, stdDiscTrim: 34%, meanDiscTrim: 50%, stdRand: 4%, meanRand, 3%

in a speller. Results of the participants performance were looked for correlation but due to the number of participants being lower than ten a correlation is difficult to find.

Time Filter

The participants were exposed to stimuli in order to elicit P300 waves, a high pass filter was used to reduce drifts, moreover the electrodes in the middle were the ones selected to plot the main characteristics of the classification data. The artifact rejection was done based on variance criterion meaning that the ones found over three standard deviations were removed from the data. Additionally the filtered data was segmented; each segment or epoch was concatenated one on top of the other, and averaged.

Targets and non-Targets

The distinction between targets and non-Targets after filtering was looked for in the lapse between 200 Ms. and 400 Ms; the lapse corresponding to the P300 varied across subjects as can be evinced in figure 4.9. The mean Frechet scores for the continuous condition is presented next to the figures showing the P300s near the electrode Cz.

ROC scores were used to separate performance in subjects in calibration data shown next. The advantage ROC scores has is that is useful to quantify the [separateness] of one dimensional distributions (binary scores) a useful metric to take into consideration in a five class classification. This score has also been taken in consideration by Schreuder(17).

Though an important detail not shown, is the persistence of eye movements in the online data, in a navigational study eye movements will be a major issue as participants cannot help but move their eyes because they will always be checking position on the screen and it was a cognitive load that was tried to be lessened by

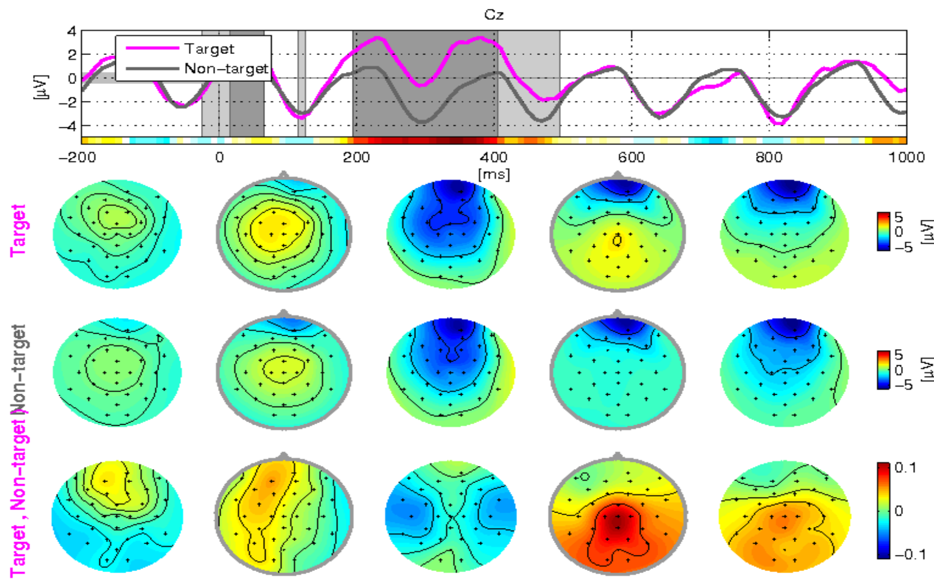

FIGURE 4.9: ERP average across epochs by nbb; P300 Classifier accuracy: 68.6%, average Frechet distances Cont: 25.54. Typical ERP plot among subjets.

making them rehearse in the actual maze so that the can recall the position of the objects and rooms without having to move much their eyes, but there is no clear option in where participants wont move their eyes in online data.

An additional detail worth including is that: although the number of participants was not big enough to find correlations in, a trend among participants was found showing that they found significantly more difficult the continuous condition followed by the discrete one and the joystick condition. This information was obtained with the use of a follow-up questionnaire.

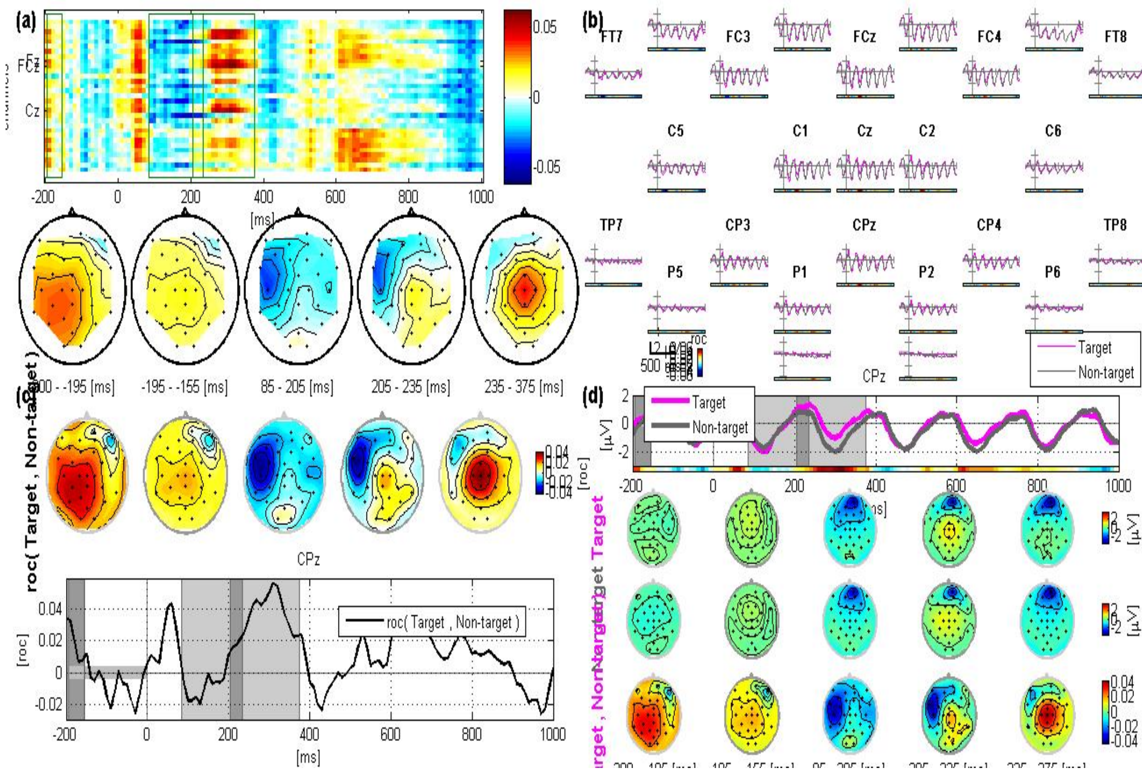

FIGURE 4.10: Event Related Potentials grand average. a) Raster Plot of averaged epochs showing increased activity around 300ms. b) Activity of electrodes around the scalp, for a higher resolution of that image, see on Annex 1. C) ROC score for Target-Non-Target peaking over 0.04 on the location of the electrode CPz at 300ms. Additional scores with scalp maps over time, showing the presence of eye-movement certainly due to navigational necessities

5

Conclusions

Here is presented a method for non-invasive navigational for a brain computer interface design that uses ERP classification to navigate through 3D environments. The results presented in both psychometric and electrophysiological analysis of the implementation of a ERP based BCI point at the potential future implementations of such technology. The results demonstrate the feasibility of the use of P300 as well as ERPs being classified and later buffered in memory to generate output in virtual environments. Optimization based on the output from the classifiers is likely to be improved by the use of more sophisticated algorithms. Participants with accuracy circling 80% in the classification/calibration phase outperformed other participants with lower scores suggesting the impact of P300s in the overall control of the designed BCI.

As classification accuracy increased, the Frechet distances decreased; so did region times and path length. The break between the targets and non-targets in the epoch grand mean is present indicating that the P300 activation was the responsible for the activity and it corresponded to activity in the brain similar to the ones reported by Schreuder (2010).

Overall, we can state that a P300- ERP based navigational BCI is possible to create, for mainly two reasons: P300 based BCI has proven to be effective among different tasks mainly communicational, take AMUSE as an example; Taking these classifications into the spatial arena is a step forward into developing new BCI technologies. As it has been shown, the main pebble on the road is the creation of meaningful control mechanisms to translate these classifications into movement. It has been long known in Neuroscience and Artificial Intelligence that movement and vision, two human capabilities that seem so clearly easy for humans or animals to perform are in practice two of the most challenging engineering problems that researchers can face. Consequently, BCI technologies that have to deal with similar problems in the future might take that into account when developing movement that: a) cognitive load in the subject shouldnt be heavily burdened so that a BCI application is possible and b) control algorithms that take P300 signals or whole ERP data should have an embedded degree of intelligence, possibly smart systems that can change output by changing the navigational algorithm on the fly.

A closer analysis of the P300 navigation BCI performance showed mainly that P300 for continuous stream of data is possible although it may require tuning to make it more precise. Additionally a discrete P300 condition that classified step by step has proven to be more accurate and when it is trimmed as its accuracy and its speed in top performers is rather comparable to the benchmark condition, suggesting that control based in P300 is possible and it is likely to have better performance boundaries.

Appendix A

Various Addendums

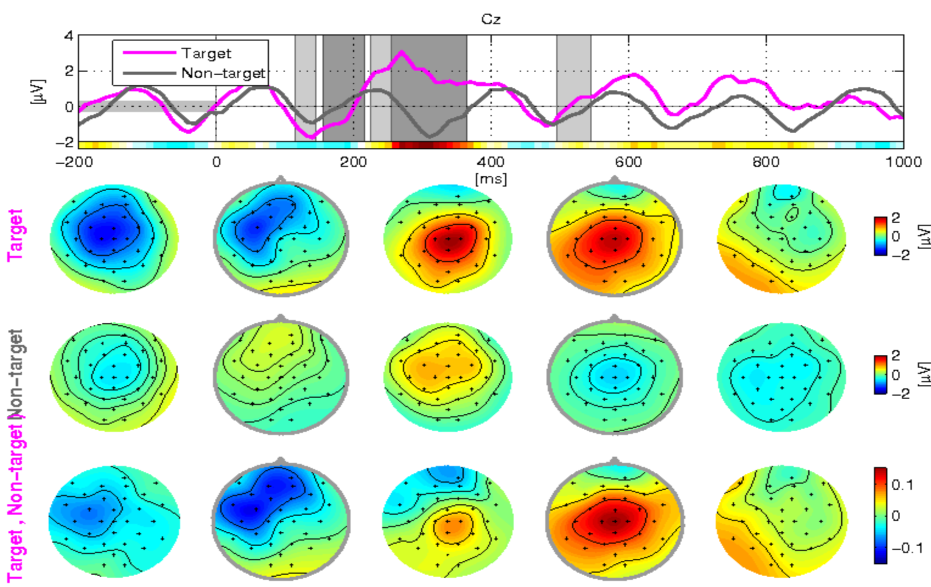

FIGURE A.1: ERP average across epochs by aab; P300 Classifier accuracy: 82.6%, average Frechet distances Cont: 20.1

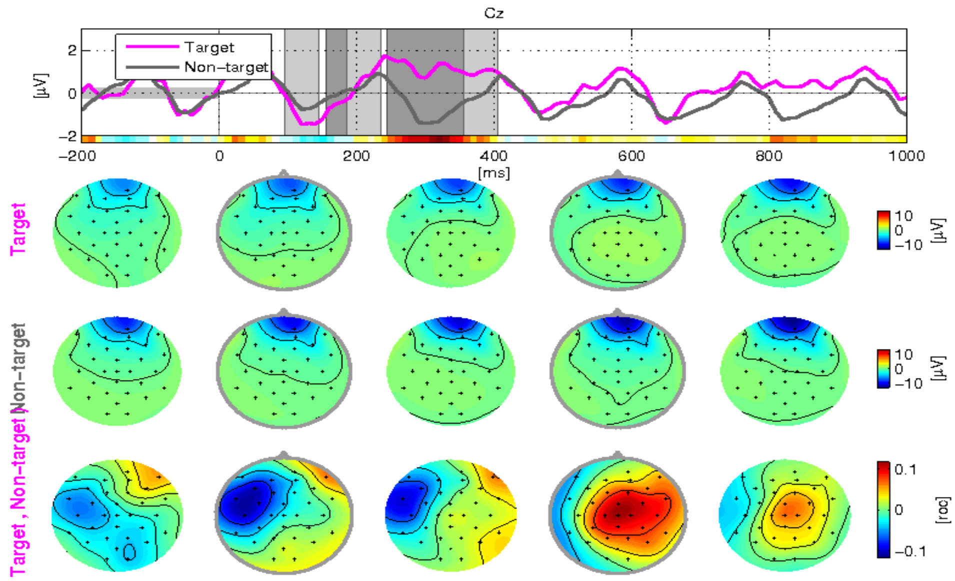

FIGURE A.2: ERP average across epochs by nba; P300 Classifier accuracy: 72.6%, average Frechet distances Cont: 28.51

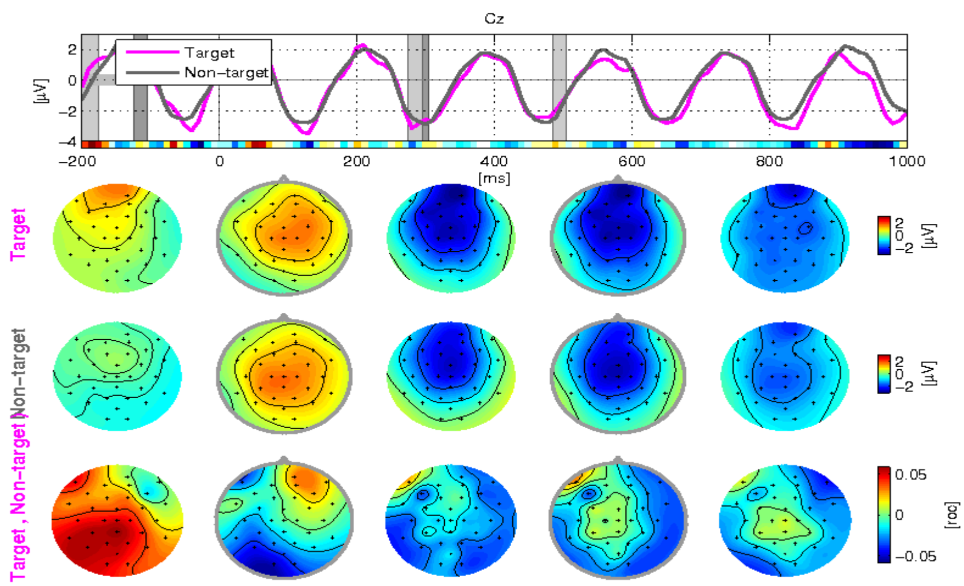

FIGURE A.3: ERP average across epochs by nbc; P300 Classifier accuracy: 58.46%, average Frechet distances Cont: 35.91

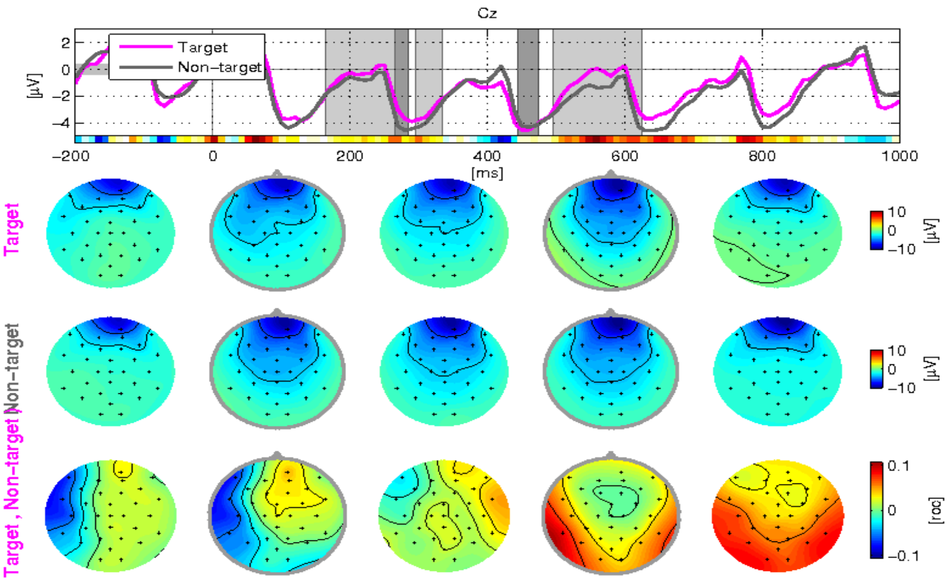

FIGURE A.4: ERP average across epochs by nbd; P300 Classifier accuracy: 66.76%, average Frechet distances Cont: 27.17

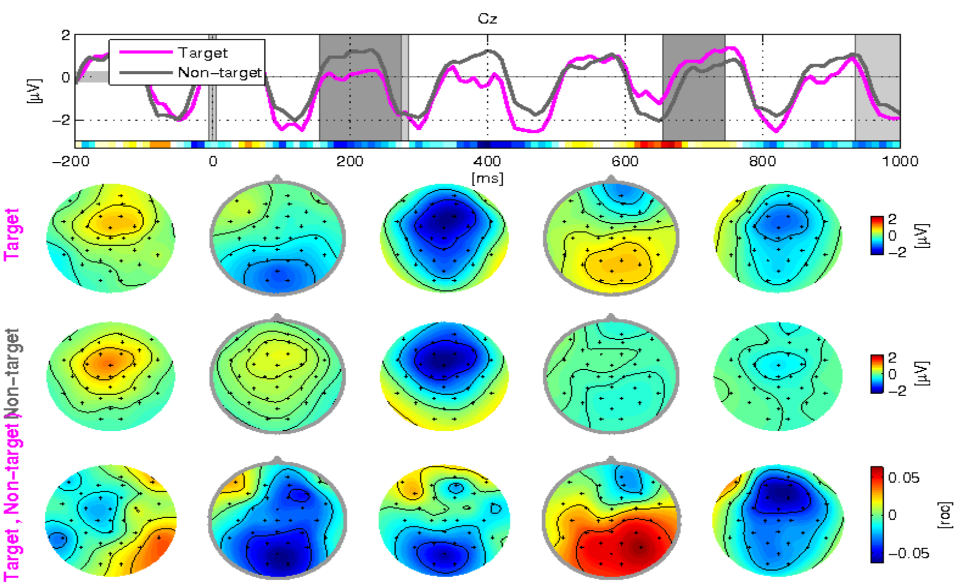

FIGURE A.5: ERP average across epochs by nbe; P300 Classifier accuracy: 54.86%, average Frechet distances Cont: 33.9

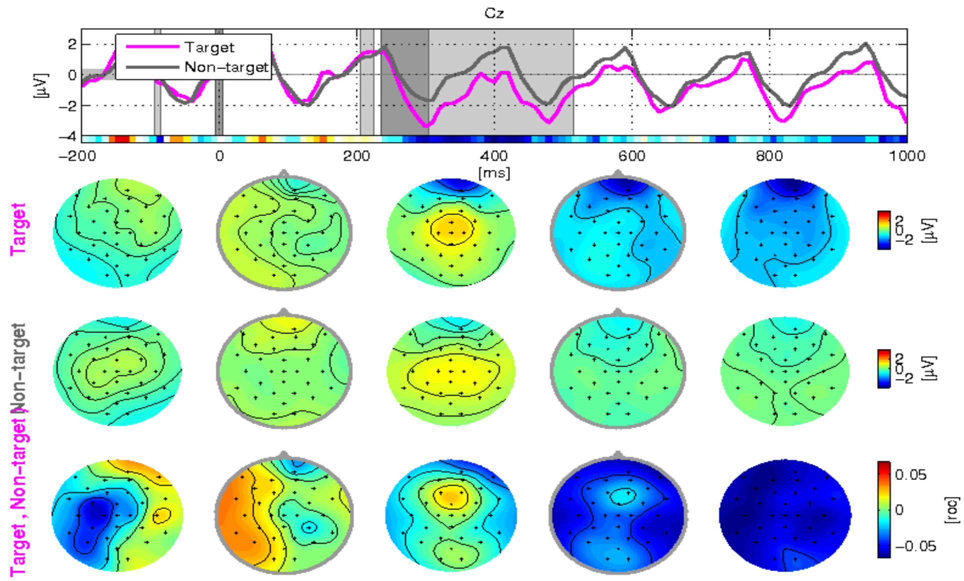

FIGURE A.6: ERP average across epochs by nbf; P300 Classifier accuracy: 61.06%, average Frechet distances Cont: 25.7

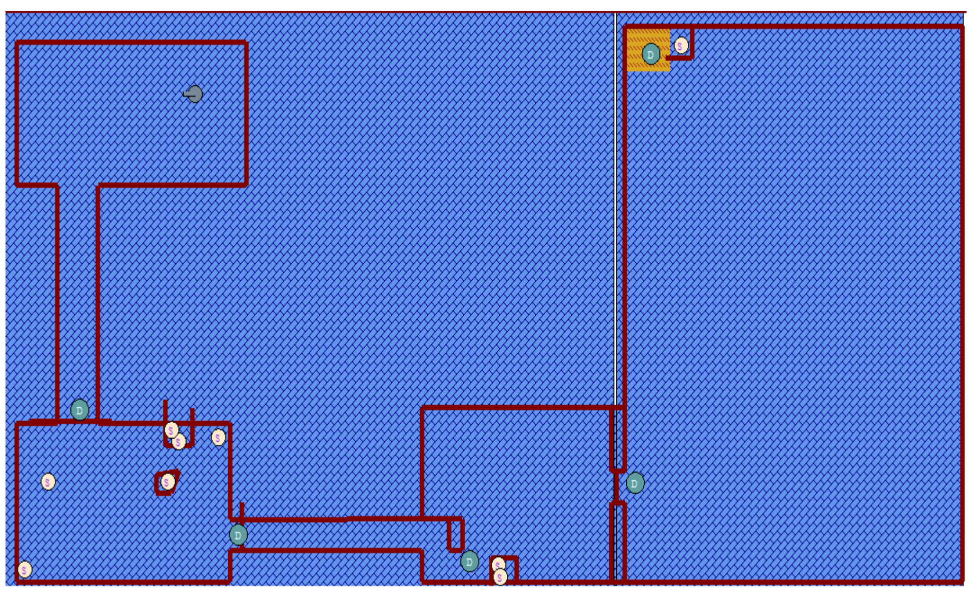

FIGURE A.7: Layout of the first experimental Maze, upper perspective

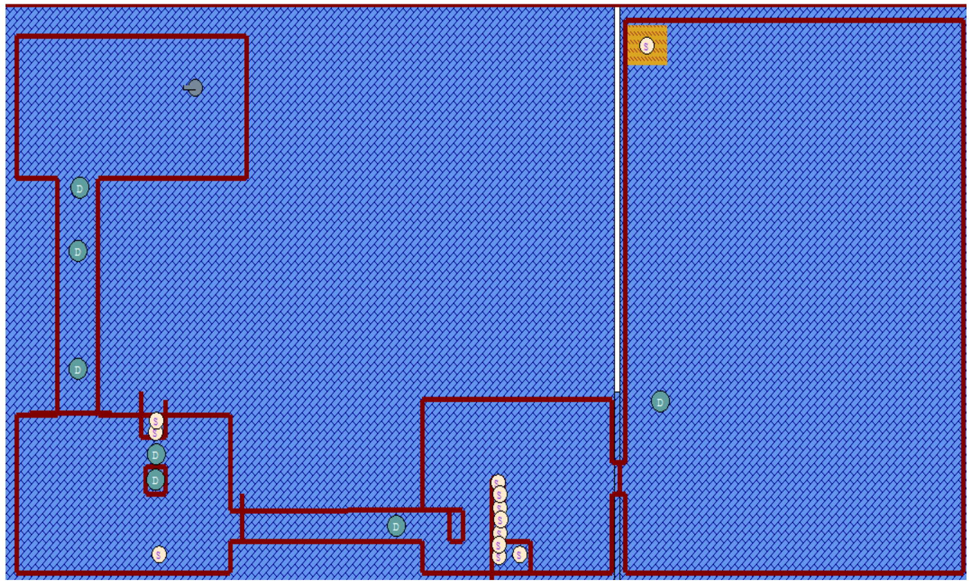

FIGURE A.8: Layout of the second experimental Maze, upper perspective

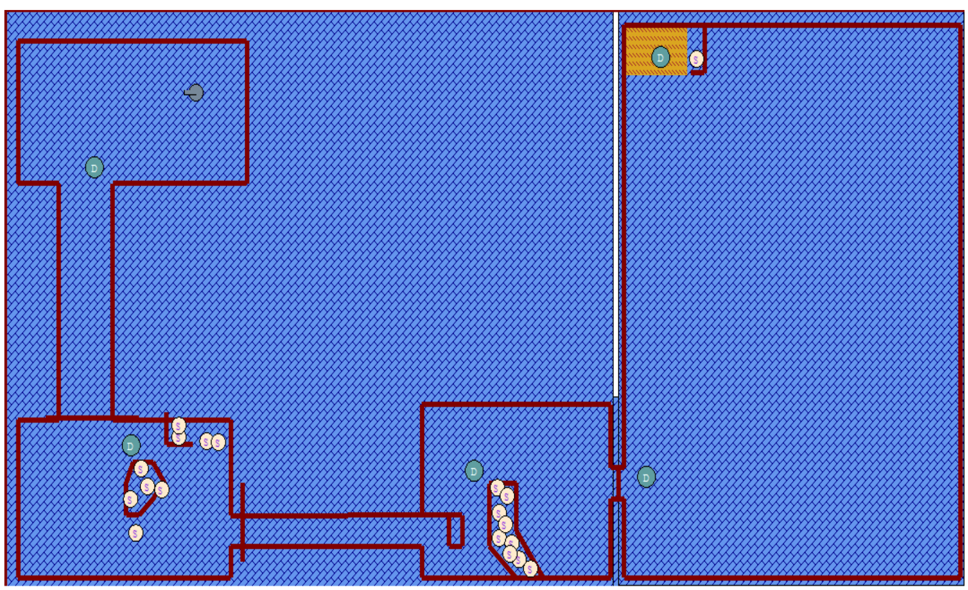

FIGURE A.9: Layout of the third experimental Maze, upper perspective

Bibliography

[1] Abdullah Akce, Miles Johnson, Or Dantsker and Timothy Bretl *A Brain-Machine Interface to Navigate a Mobile Robot in a Planar Workspace: Enabling Humans to Fly Simulated Aircraft with EEG* University of Illinois at Urbana-Champaign, Urbana, IL, 61801, USA

[2] Abdullah Akce, Miles Johnson, and Timothy Bretl *Remote Teleoperation of an Unmanned Aircraft with a Brain-Machine Interface: Theory and Preliminary Results* 2013: Department of Computer Science and M. Johnson and T. Bretl are with the Department of Aerospace Engineering, University of Illinois at Urbana-Champaign, Urbana, IL, 61801, USA faakce2,mjohns50,tbretlg@illinois.edu

[3] Hasan Ayaz and Adrian Curtin *Maze Suite Quick Start Guide* 2011 Drexel University. Available at `http://`www.mazesuite.com/

[4] Hasan Ayaz, Patricia A. Shewokis, Adrian Curtin, Meltem Izzetoglu, Kurtulus Izzetoglu, and Banu Onaral *Using MazeSuite and Functional Near Infrared Spectroscopy to Study Learning in Spatial Navigation* J Vis Exp. 2011; (56): 3443. Published online 2011 October 8. doi: 10.3791/3443

[5] Boris Aronov, Sariel Har-Peled, Christian Knauer, Yusu Wang, and Carola Wenk *Frechet Distance for Curves, Revisited 21.479.* 2010.

[6] Theodore W. Berger, John K. Chapin, Greg A. Gerhardt *Brain Computer Interfaces. An International Assessment of Research and Development Trends* 2008 Springer Science - Business Media B.V. ISBN: 978-1-4020-8704-2 e-ISBN: 978-1-4020-8705-9 Library of Congress Control Number: 2008930994.

[7] Adrian Curtin, Hasan Ayaz, Yichuan Liu, Patricia A. Shewokis, Banu Onaral *A P300-based EEG-BCI for Spatial Navigation Control* 34th Annual International Conference of the IEEE EMBS San Diego, California USA, 28 August - 1 September, 2012.

[8] Luca Citi, Riccardo Poli, Caterina Cinel, and Francisco Sepulveda *P300-Based BCI Mouse With Genetically-Optimized Analogue Control* 2008, IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING, VOL. 16, NO. 1.

[9] Blankertz, B., Lemm, S., Treder, M. S., Haufe, S., and Mller, K.-R *Single-trial analysis and classification of ERP components a tutorial*2011. Neuroimage 56, 814825.

[10] J. Elshout; G. Garcia Molina*Review of Brain-Computer Interfaces based on the P300 evoked potentiall* 2009: Philips Research Europe. PR-TN 2009/00066: PR-TN 2009/00066.

[11] Höhne J., Schreuder M., Blankertz B. and Tangermann M. *A novel 9-class auditory ERP paradigm driving a predictive text entry system* frontiers in Neuroscience. doi: 10.3389/fnins.2011.00099

[12] Höhne, Schreuder M., Blankertz, M., Mller K. and Michael Tangermann *Novel Paradigms for Auditory ERP Spellers with Spatial Hearing: Two Online Studies* International Journal of Bioelectromagnetism. Vol. 13, No. 2, pp. 96 97, 2011.

[13] Karl LaFleur, Kaitlin Cassady, Alexander Doud, Kaleb Shades, Eitan Rogin and Bin He *Quadcopter control in three-dimensional space using a noninvasive motor imagery-based braincomputer interface* /url http://iopscience.iop.org/1741-2552/10/4/046003/article

[14] Audrey S. Royer, Alexander J. Doud, Minn L. Rose, and Bin He *EEG Control of a Virtual Helicopter in 3-Dimensional Space Using Intelligent Control Strategies.* 2010. Copyright (c) 2010 IEEE.

[15] Gert Pfurtscheller, Robert Leeb, Josef Faller and Christa Neuper *Brain-Computer Interface Systems used for Virtual Reality Control* /url http://www.intechopen.com/

[16] Schreuder M., Rost T. and Tangermann M. *Listen, you are writing! Speeding upon line spelling with a dynamic auditory BCI* 2011, Frontiers in Neuroscience. doi: 10.3389/fnins.2011.00112

[17] Schreuder M., Blankertz B., Tangermann M. *A New Auditory Multi-Class Brain-Computer Interface Paradigm: Spatial Hearing as an Informative Cue* 2010 PLoS ONE 5(4): e9813. doi:10.1371/journal.pone.0009813

[18] Zhao QiBin, Zhang LiQing, Cichocki Andrzej *EEG-based asynchronous BCI control of a car in 3D virtual reality environments* 2009: Chinese Science Bulletin, Springer

Declaration of Authorship

I hereby certify that the work presented here is, to the best of my knowledge and belief, original and the result of my own investigations, except as acknowledged, and has not been submitted, either in part or whole, for a degree at this or any other university.

signature

city, date